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Please find below and/or attached an Office communication concerning this application or proceeding.

Office Action Summary	Application No. 10/656,067	Applicant(s) YADEGAR ET AL.	
	Examiner Sergey Datskovskiy	Art Unit 2121	

-- The MAILING DATE of this communication appears on the cover sheet with the correspondence address --

Period for Reply

A SHORTENED STATUTORY PERIOD FOR REPLY IS SET TO EXPIRE 3 MONTH(S) OR THIRTY (30) DAYS, WHICHEVER IS LONGER, FROM THE MAILING DATE OF THIS COMMUNICATION.

- Extensions of time may be available under the provisions of 37 CFR 1.136(a). In no event, however, may a reply be timely filed after SIX (6) MONTHS from the mailing date of this communication.
- If NO period for reply is specified above, the maximum statutory period will apply and will expire SIX (6) MONTHS from the mailing date of this communication.
- Failure to reply within the set or extended period for reply will, by statute, cause the application to become ABANDONED (35 U.S.C. § 133). Any reply received by the Office later than three months after the mailing date of this communication, even if timely filed, may reduce any earned patent term adjustment. See 37 CFR 1.704(b).

Status

1)☒ Responsive to communication(s) filed on 05 September 2003.

2a)☐ This action is **FINAL**. 2b)☒ This action is non-final.

3)☐ Since this application is in condition for allowance except for formal matters, prosecution as to the merits is closed in accordance with the practice under *Ex parte Quayle*, 1935 C.D. 11, 453 O.G. 213.

Disposition of Claims

4)☒ Claim(s) 1-47 is/are pending in the application.

4a) Of the above claim(s) _____ is/are withdrawn from consideration.

5)☐ Claim(s) _____ is/are allowed.

6)☒ Claim(s) 1-47 is/are rejected.

7)☐ Claim(s) _____ is/are objected to.

8)☐ Claim(s) _____ are subject to restriction and/or election requirement.

Application Papers

9)☐ The specification is objected to by the Examiner.

10)☒ The drawing(s) filed on 05 September 2003 is/are: a)☒ accepted or b)☐ objected to by the Examiner.

Applicant may not request that any objection to the drawing(s) be held in abeyance. See 37 CFR 1.85(a).

Replacement drawing sheet(s) including the correction is required if the drawing(s) is objected to. See 37 CFR 1.121(d).

11)☐ The oath or declaration is objected to by the Examiner. Note the attached Office Action or form PTO-152.

Priority under 35 U.S.C. § 119

12)☐ Acknowledgment is made of a claim for foreign priority under 35 U.S.C. § 119(a)-(d) or (f).

a)☐ All b)☐ Some * c)☐ None of:

1.☐ Certified copies of the priority documents have been received.

2.☐ Certified copies of the priority documents have been received in Application No. _____.

3.☐ Copies of the certified copies of the priority documents have been received in this National Stage application from the International Bureau (PCT Rule 17.2(a)).

* See the attached detailed Office action for a list of the certified copies not received.

Attachment(s)

1) ☒ Notice of References Cited (PTO-892)
2) ☐ Notice of Draftsperson's Patent Drawing Review (PTO-948)
3) ☒ Information Disclosure Statement(s) (PTO-1449 or PTO/SB/08) Paper No(s)/Mail Date _____.
4) ☐ Interview Summary (PTO-413) Paper No(s)/Mail Date. _____ .
5) ☐ Notice of Informal Patent Application (PTO-152)
6) ☐ Other: _____.

DETAILED ACTION

1. Claims 1-47 have been submitted for examination.

2. Claims 1-47 have been rejected.

Information Disclosure Statement

The information disclosure statement filed September 5, 2003 fails to comply with 37 CFR 1.98(a)(2), which requires a legible copy of each cited foreign patent document; each non-patent literature publication or that portion which caused it to be listed; and all other information or that portion which caused it to be listed. It has been placed in the application file, but the information referred to therein has not been considered. Specifically, the missing items that have not been considered are: articles AC, AE, AN from page 1 and AH from page 3.

Claim Objections

3. Claims 3, 17 and 43 are objected to because of the following informalities:

   a. Claims 3 and 43 contain a grammatically incorrect phrase "data are know to exist". It is suggested to change it to "data are known to exist".

   b. One of the limitations of claim 17 is "mining" on line 7. It would be appropriate to change it to "data mining", unless Applicant actually means "mining", *i.e.* extracting minerals from the earth.

Appropriate correction is required.

Claim Rejections - 35 USC § 101

35 U.S.C. 101 reads as follows:

> Whoever invents or discovers any new and useful process, machine, manufacture, or composition of matter, or any new and useful improvement thereof, may obtain a patent therefor, subject to the conditions and requirements of this title.

4. Claims 1-38, 40-41, 43-44 and 47 are rejected under 35 U.S.C. §101 because the claimed invention is directed to non-statutory subject matter.

5. Claims 1-24 and 43 are directed towards a method of modeling data. Such method represents an abstract algorithm. Abstract ideas (see Warmerdam, 33 F.3d at 1360, 31 USPQ2d at 1759) or mere manipulation of abstract ideas (see Schrader, 22 F.3d at 292-93, 30 USPQ2d at 1457-58) are not patentable. However, for claims including such excluded subject matter to be eligible, the claims must be for a <u>practical application</u> of the abstract idea. Such practical application can be identified in the following ways:

a. The claimed invention "transforms" an article of physical object to a different state or thing.

b. The claimed invention otherwise produces a useful, concrete and tangible result.

The acts of tessellation, filtering and other disclosed data manipulations do not produce any physical transformations. The next step would be to determine whether the claimed invention produces a useful, concrete and tangible result. Result of the claims is data. Such result is abstract and, therefore, cannot satisfy the condition of being tangible.

Claims 25-36 and 44 are directed towards a method for compressing data. Similarly to the method of modeling data, these claims describe a mathematical

algorithm of transforming data. According to the analysis give above, these claims are also non-statutory as being directed to a manipulation of abstract ideas.

Claims 37-38 are directed towards modeling an image for compression. They describe an algorithm that produces an image as a result. However, in view of broadness of the term "image", the result of these claims is abstract. It is not limited to a real-world result, such as, for example, a visual image. An "image" can also include a digital representation of bits in a computer memory, or a mental picture of something not real or present. Such result is not tangible.

Claims 40-41 are also directed towards modeling an image for compression. However, unlike claims 37-38, they result in a decomposition tree. Such tree is a representation of an image data. These claims are non-statutory for the same reason as the claims 37-38 due to an abstract nature of the term "image".

Claim 47 is directed to a data structure. Data structures not claimed as embodied in computer-readable media are descriptive material per se and are not statutory because they are not capable of causing functional change in the computer (See Warmerdam, 33 F.3d at 1361, 31 USPQ2d at 1760). Such claimed data structures do not define any structural and functional interrelationships between the data structure and other claimed aspects of the invention, which permit the data structure's functionality to be realized. Data structure from claim 47 does not contain any indication of the functional relationship except for being used "in conjunction with file compression" in the abstract of the claim. There is no indication of how it is going to be used. For example it can even be a part of the data that is being compressed.

Therefore, the "data structure" of claim 47 represent a nonfunctional descriptive material, *i.e.* a mere arrangements or compilations of facts or data, without any functional interrelationship. Nonfunctional descriptive material is not statutory and should be rejected under 35 U.S.C. §101.

Claim Rejections - 35 USC § 112

The following is a quotation of the first paragraph of 35 U.S.C. 112:

> The specification shall contain a written description of the invention, and of the manner and process of making and using it, in such full, clear, concise, and exact terms as to enable any person skilled in the art to which it pertains, or with which it is most nearly connected, to make and use the same and shall set forth the best mode contemplated by the inventor of carrying out his invention.

The following is a quotation of the second paragraph of 35 U.S.C. 112:

> The specification shall conclude with one or more claims particularly pointing out and distinctly claiming the subject matter which the applicant regards as his invention.

6. Claims 2, 25, 43, 44 and 47 rejected under 35 U.S.C. 112, first paragraph, as failing to comply with the written description requirement. The claim(s) contains subject matter which was not described in the specification in such a way as to reasonably convey to one skilled in the relevant art that the inventor(s), at the time the application was filed, had possession of the claimed invention.

Claims 2 and 43 contain a term "3-dimensional video". It is not clear what Applicant means by that term. Conventional video is a 2-demensional projection. It is possible, that claims contain some kind of video projected into three dimensions. However, Specification contains no mention of "3-dimensional video", and no explanation of what that term could possibly mean.

Claims 25, 44 and 47 contain a term “energy”. This term appears multiple times in the Specification. It is usual for “energy” to be used in relation with a physical activity. Specification does not explain what “energy” means as a term being used in a compression algorithm.

7. Claims 20, 34, 43 and 44 are rejected under 35 U.S.C. 112, second paragraph, as being indefinite for failing to particularly point out and distinctly claim the subject matter which applicant regards as the invention.

Regarding claims 20, 34, 43 and 44, the phrase "other learning regimes" renders the claim(s) indefinite because the claim(s) include(s) elements not actually disclosed (those encompassed by "other"), thereby rendering the scope of the claim(s) unascertainable. See MPEP § 2173.05(d).

Claim Rejections - 35 USC § 102

The following is a quotation of the appropriate paragraphs of 35 U.S.C. 102 that form the basis for the rejections under this section made in this Office action:

> A person shall be entitled to a patent unless –
>
> (b) the invention was patented or described in a printed publication in this or a foreign country or in public use or on sale in this country, more than one year prior to the date of application for patent in the United States.
>
> (e) the invention was described in (1) an application for patent, published under section 122(b), by another filed in the United States before the invention by the applicant for patent or (2) a patent granted on an application for patent by another filed in the United States before the invention by the applicant for patent, except that an international application filed under the treaty defined in section 351(a) shall have the effects for purposes of this subsection of an application filed in the United States only if the international application designated the United States and was published under Article 21(2) of such treaty in the English language.

8. Claims 1-17, 24-32, 36-39 and 45-46 are rejected under 35 U.S.C. 102(e) as being anticipated by Bright (US Patent No. 6,897,977).

Claim 1

Bright teaches a method for modeling data using adaptive pattern-driven filters (Abstract, modeling is disclosed as compressing data), comprising:

applying an algorithm to data to be modeled based on an approach selected from the group consisting of: computational geometry (col. 4, lines 42-47; disclosed as a compression algorithm that works by geometrically splitting the image); artificial intelligence; machine learning; and data mining;

whereby the data is modeled to enable better manipulation of the data (col. 2, lines 52-55).

Claim 2

Bright teaches a method for modeling data using adaptive pattern-driven filters as set forth in claim 1, further comprising:

the data to be modeled selected from the group consisting of: 2-dimensional still images; 2-dimensional still objects; 2-dimensional time-based objects; 2-dimensional video; 2-dimensional image recognition; 2-dimensional video recognition; 2-dimensional image understanding; 2-dimensional video understanding; 2-dimensional image mining; 2-dimensional video mining; 3-dimensional still images; 3-dimensional still objects; 3-dimensional video; 3-dimensional time-based objects; 3-dimensional object recognition; 3-dimensional image recognition; 3-dimensional video recognition; 3-dimensional object understanding; 3-dimensional object mining; 3-dimensional video mining; N-dimensional

objects where N is greater than 3; N-dimensional time-based objects; Sound patterns; and Voice patterns (col. 4, lines 42-47; compressing video image data).

Claim 3

Bright teaches a method for modeling data using adaptive pattern-driven filters as set forth in claim 1, further comprising: the data to be modeled selected from the group consisting of:

generic data of generic nature wherein no specific characteristics of the generic data are know to exist within different parts of the data (col. 3, lines 7-10; disclosed as compressing general image data comprising of pixels arranged in a grid); and

class-based data of class-based nature wherein specific characteristics are known to exist within different parts of the class-based data, the specific characteristics enabling advantage to be taken in modeling the class-based data (col. 6, lines 1-13; images having a "textured" appearance, classification matches repeated patterns of pixels).

Claim 4

Bright teaches a method for modeling data using adaptive pattern-driven filters as set forth in claim 3, further comprising: an overarching modeling meta-program generating an object-program for the data (col. 8, lines 50-58; generating color encoding using YCbCr scheme).

Claim 5

Bright teaches a method for modeling data using adaptive pattern-driven filters as set forth in claim 4, further comprising: the object-program generated by the meta-program selected from the group consisting of: a codec, a modeler, and a combination of both (col. 8, lines 9-15; a color encoding model implies a codec for compressing-decompressing colors).

Claim 6

Bright teaches a method for modeling data using adaptive pattern-driven filters as set forth in claim 1, further comprising: the data is modeled to enable the data being compressed for purposes of reducing overall size of the data (col. 1, lines 12-17).

Claim 7

Bright teaches a method for modeling data using adaptive pattern-driven filters as set forth in claim 1, wherein the algorithm applied to the data further comprises:

providing a linear adaptive filter adapted to receive data and model the data that have a low to medium range of intensity dynamics (col. 3, lines 54-58; disclosed as the part of the algorithm that performs subdivision into triangles);

providing a non-linear adaptive filter adapted to receive the data and model the data that have medium to high range of intensity dynamics (col. 6, lines 1-13; disclosed

as the part of the algorithm that performs pattern recognition to map texture patterns); and

providing a lossless filter adapted to receive the data and model the data not modeled by the linear adaptive filter and the non-linear adaptive filter, including residual data from the linear and non-linear adaptive filters (col. 7, lines 23-41; using Huffman lossless compression).

Claim 8

Bright teaches a method for modeling data as set forth in claim 7, wherein the linear adaptive filter further comprises: tessellation of the data (col. 4, lines 42-47).

Claim 9

Bright teaches a method for modeling data as set forth in claim 8, wherein the tessellation of the data further comprises: tessellation of the data as viewed from computational geometry (col. 4, lines 42-54; since the tessellation is done using a geometric algorithm, it belongs to computational or algorithmic geometry).

Claim 10

Bright teaches a method for modeling data as set forth in claim 8, wherein the tessellation of the data is selected from the group consisting of planar tessellation and spatial (volumetric) tessellation (col. 5, lines 8-17; disclosed are both forms of tessellation, since each triangle has its own plane with a Z component).

Claim 11

Bright teaches a method for modeling data as set forth in claim 8, wherein the tessellation of the data is achieved by a methodology selected from the group consisting of: a combination of regression techniques; a combination of optimization methods including linear programming; a combination of optimization methods including non-linear programming; and a combination of interpolation methods (col. 5, lines 30-47; disclose the use of interpolation).

Claim 12

Bright teaches a method for modeling data as set forth in claim 10, wherein the planar tessellation of the data comprises triangular tessellation (col. 5, lines 8-17).

Claim 13

Bright teaches a method for modeling data as set forth in claim 10, wherein the spatial tessellation of the data comprises tessellation selected from the group consisting of tetrahedral tessellation and tessellation of a 3-dimensional geometrical shape (col. 5, lines 14-17; each triangle defines a 3-d plane, forming a 3-dimentional shape. Adjusting 3-d triangles form a tetrahedral).

Claim 14

Bright teaches a method for modeling data as set forth in claim 8, wherein the tessellation of the data is executed by an approach selected from the group consisting of breadth-first, depth-first, best-first, any combination of these (col. 6, lines 34-36; disclose a depth-first approach), and any method of tessellation that approximates the data subject to an error tolerance (col. 5, lines 49-54; using a similarity threshold).

Claim 15

Bright teaches a method for modeling data as set forth in claim 12, wherein the tessellation of the data is selected from the group consisting of Peano-Cezaro decomposition, Sierpiski decomposition, Ternary triangular decomposition, Hex-nary triangular decomposition, any other triangular decomposition, and any other geometrical shape decomposition (col. 5, lines 8-17).

Claim 16

Bright teaches a method for modeling data as set forth in claim 7, wherein the non-linear adaptive filter further comprises: a filter modeling non-planar parts of the data using primitive data patterns (col. 6, lines 1-9, using a set of predefined texture patterns).

Claim 17

Bright teaches a method for modeling data as set forth in claim 16, further comprising: the modeling of the non-planar parts of the data performed using a methodology selected from the group consisting of: artificial intelligence; machine learning; knowledge discovery; mining; and pattern recognition (col. 6, lines 1-13; using pattern recognition).

Claim 24

Bright teaches a method for modeling data as set forth in claim 16, further comprising:

providing a set of tiles approximating the data (col. 5, lines 8-17);

providing a queue of the set of tiles for input to the non-linear adaptive filter (col. 6, lines 34-36; processing tiles in a specific order implies queuing);

the non-linear adaptive filter processing each tile in the queue (col. 3, lines 50-51);

for each tile selected, the non-linear adaptive filter determining if the selected tile is within a tolerance of error (col. 3, lines 38-44);

for each selected tile within the tolerance of error, the tile is returned as a terminal tile (col. 3, lines 38-40);

for each selected tile outside the tolerance of error, the selected tile is decomposed into smaller subtiles which are returned to the queue for further processing (col. 3, lines 54-58).

Claim 25

Bright teaches a method for compressing data, comprising:

providing a linear adaptive filter adapted to receive data and compress the data that have low to medium energy dynamic range (col. 3, lines 54-58; disclosed as the part of the algorithm that performs subdivision into triangles);

providing a non-linear adaptive filter adapted to receive the data and compress the data that have medium to high energy dynamic range (col. 6, lines 1-13; disclosed as the part of the algorithm that performs pattern recognition to map texture patterns); and

providing a lossless filter adapted to receive the data and compress the data not compressed by the linear adaptive filter and the non-linear adaptive filter; whereby data is being compressed for purposes of reducing its overall size (col. 7, lines 23-41; using Huffman lossless compression).

Claim 26

Bright teaches a method for compressing data as set forth in claim 25, wherein the linear adaptive filter further comprises: tessellation of the data (col. 4, lines 42-47).

Claim 27

Bright teaches a method for compressing data as set forth in claim 26, wherein the tessellation of the data is selected from the group consisting of planar tessellation and spatial tessellation (col. 5, lines 8-17; disclosed are both forms of tessellation, since each triangle has its own plane with a Z component).

Claim 28

Bright teaches a method for compressing data as set forth in claim 27, wherein the planar tessellation of the data comprises triangular tessellation (col. 5, lines 8-17).

Claim 29

Bright teaches a method for compressing data as set forth in claim 27, wherein the spatial tessellation of the data comprises tetrahedral tessellation (col. 5, lines 14-17; each triangle defines a 3-d plane, forming a 3-dimentional shape. Adjusting 3-d triangles form a tetrahedral).

Claim 30

Bright teaches a method for compressing data as set forth in claim 26, wherein the tessellation of the data is selected from the group consisting of breadth-first, depth-first, best-first, any combination of these (col. 6, lines 34-36; disclose a depth-first approach), and any method of tessellation that approximates the data filtered by the

linear adaptive filter within selectably acceptable limits of error (col. 5, lines 49-54; using a similarity threshold).

Claim 31

Bright teaches a method for compressing data as set forth in claim 28, wherein the tessellation of the data is selected from the group consisting of Peano-Cezaro decomposition, Sierpiski decomposition, Ternary triangular decomposition, Hex-nary triangular decomposition, any other triangular decomposition, and any other geometrical shape decomposition (col. 5, lines 8-17).

Claim 32

Bright teaches a method for compressing data as set forth in claim 25, wherein the non-linear adaptive filter further comprises: a filter modeling non-planar parts of the data using primitive image patterns (col. 6, lines 1-9, using a set of predefined texture patterns).

Claim 36

Bright teaches a method for compressing data as set forth in claim 32, further comprising:

providing a set of tiles approximating the data (col. 5, lines 8-17);

providing a queue of the set of tiles for input to the non-linear adaptive filter (col. 6, lines 34-36; processing tiles in a specific order implies queuing);

the non-linear adaptive filter processing each tile in the queue (col. 3, lines 50-51);

for each tile selected, the non-linear adaptive filter determining if the selected tile is within a tolerance of error (col. 3, lines 38-44);

for each selected tile within the tolerance of error, the tile is returned as a terminal tile (col. 3, lines 38-40);

for each selected tile outside the tolerance of error, the selected tile is decomposed into smaller subtiles which are returned to the queue for further processing (col. 3, lines 54-58).

Claim 37

Bright teaches a method for modeling an image for compression, comprising:

obtaining an image (col. 4, lines 42-47; video image data); performing computational geometry to the image (col. 4, lines 42-54; since the tessellation is done using a geometric algorithm, it belongs to computational or algorithmic geometry); and

applying machine learning to decompose the image (col. 6, lines 1-9; use of pattern-matching algorithms implies machine learning, *i.e.* a machine has learned to recognize specific image patterns);

whereby the image is represented in a data form having a reduced size (Abstract, compressing data).

Claim 38

Bright teaches a method for modeling an image for compression as set forth in claim 37, further comprising: recomposing the image from the data form representation by machine learning (col. 11, lines 1-4).

Claim 39

Bright teaches a method for modeling an image for compression as set forth in claim 38, further comprising: the image selected from the group consisting of: a video image; and a series of video images (col. 4, lines 42-47; using video image frames).

Claim 45

Bright teaches a method for modeling an image for compression, comprising:

obtaining an image (col. 4, lines 42-47; video image data); performing computational geometry to the image (col. 4, lines 42-54; since the tessellation is done using a geometric algorithm, it belongs to computational or algorithmic geometry);

applying machine learning to decompose the image such that the image is represented in a data form having a reduced size (col. 6, lines 1-9; use of pattern-matching algorithms implies machine learning, *i.e.* a machine has learned to recognize specific image patterns); and

recomposing the image from the data form representation by machine learning (col. 11, lines 1-4);

wherein the image selected from the group consisting of: a video image and a series of video images (col. 4, lines 42-47; using video image frames).

Claim 46

Bright teaches a method for modeling an image for compression, comprising:

formulating a data structure by using a methodology selected from the group consisting of: computational geometry, artificial intelligence, machine learning, data mining, pattern recognition techniques (col. 6, lines 1-13; using pattern recognition); and

creating a decomposition tree based on the data structure, the decomposition tree is achieved by application of an approach selected from the group consisting of: Peano-Cezaro decomposition, Sierpiski decomposition, Ternary triangular decomposition, Hex-nary triangular decomposition, any other triangular decomposition approach, any other geometrical shape decomposition method (col. 5, lines 8-17; using a triangular decomposition); wherein

an image to be modeled is selected from the group consisting of a video image and a series of video images (col. 4, lines 42-47; using video image frames).

9. Claims 40-42 are rejected under 35 U.S.C. 102(b) as being anticipated by Dansereau et al. ("Perceptual Image Compression Through Fractal Surface Interpolation").

Claim 40

Dansereau teaches a method for modeling an image for compression, comprising:

formulating a data structure by using a methodology selected from the group consisting of: computational geometry; artificial intelligence; machine learning; data mining; and pattern recognition techniques (page 900, right column; disclosed tessellation algorithm belongs to the field of computational geometry); and

creating a decomposition tree based on the data structure (page 900, right column, last line through page 900, left column, first line; disclosed as forming a quad-tree).

Claim 41

Dansereau teaches a method for modeling an image for compression as set forth in claim 40, wherein creating the decomposition tree is achieved by application of an approach selected from the group consisting of: Peano-Cezaro decomposition; Sierpiski decomposition; Ternary triangular decomposition; Hex-nary triangular decomposition; any other triangular decomposition approach; and any other geometrical shape decomposition method (page 900, right column, second paragraph).

Claim 42

Dansereau teaches a method for modeling an image for compression as set forth in claim 41, wherein an image to be modeled is selected from the group consisting of: a

video image; and a series of video images (page 901, chapter V, lines 1-3; disclosed algorithm has been tested on video images).

Claim Rejections - 35 USC § 103

The following is a quotation of 35 U.S.C. 103(a) which forms the basis for all obviousness rejections set forth in this Office action:

> (a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains. Patentability shall not be negatived by the manner in which the invention was made.

Claims 18-23, 33-35 and 43-44 are rejected under 35 U.S.C. 103(a) as being unpatentable over Bright (US Patent No. 6,897,977) in view of Tsishkou et al. ("Mosaic Ultrasound Medical Image Compression Using TTA10 Algorithm").

Claim 18

Bright teaches a method for modeling data as set forth in claim 16.

Bright does not expressly teach further comprising: training the non-linear adaptive filter at a time selected from the group consisting of: prior to run-time application of the non-linear adaptive filter; and at run-time application of the non-linear adaptive filter, the non-linear adaptive filter becoming evolutionary and self-improving.

Tsishkou teaches training the non-linear adaptive filter at a time selected from the group consisting of: prior to run-time application of the non-linear adaptive filter; and at run-time application of the non-linear adaptive filter, the non-linear adaptive filter

becoming evolutionary and self-improving (page 1174, left column, lines 13-16; page 1175, right column, lines 6-10; the filter is self-improving by training a tree used for image classification).

Bright and Tsishkou are analogous art since they are both the field of image compression. At the time of the invention, it would have been obvious to a person of ordinary skill in the art to include the hierarchical data structure used in the learning algorithm from Tsishkou (page 1174, left column, lines 13-16; page 1175, right column, lines 6-10) and use it as a pattern-recognition algorithm in Bright (col. 6, lines 7-9). The reason for doing so would be to assist in working with large number of training images (Tsishkou, page 1174, left column, lines 10-14). Therefore, it would have been obvious to modify Bright in view of Tsishkou by using a learning algorithm with a hierarchical tree data structure for pattern-recognition.

Claim 19

Bright teaches a method for modeling data as set forth in claim 16.

Bright does not expressly teach that the non-linear adaptive filter further comprises: a hash-function data-structure based on prioritization of tessellations, the prioritization based on available information within and surrounding a tessellation with the prioritization of the tessellation for processing being higher according to higher availability of the available information.

Tsishkou teaches that the non-linear adaptive filter further comprises: a hash-function data-structure based on prioritization of tessellations, the prioritization based on

available information within and surrounding a tessellation with the prioritization of the tessellation for processing being higher according to higher availability of the available information (page 1175, right column, lines 6-11; the data structure is disclosed as a tree based on tessellation).

At the time of the invention, it would have been obvious to a person of ordinary skill in the art to include the hierarchical data structure used in the learning algorithm from Tsishkou (page 1174, left column, lines 13-16; page 1175, right column, lines 6-10) and use it as a pattern-recognition algorithm in Bright (col. 6, lines 7-9) using the same motivation as in claim 18 above.

Claim 20

Bright teaches a method for modeling data as set forth in claim 16.

Bright does not expressly teach that the non-linear adaptive filter further comprises: a hierarchy of learning units based on primitive data patterns; and the learning units integrating clusters selected from the group consisting of: neural networks; mixtures of Gaussians; support vector machines; Kernel functions; genetic programs; decision trees; hidden Markov models; independent component analysis; principle component analysis; and other learning regimes.

Tsishkou teaches that the non-linear adaptive filter further comprises: a hierarchy of learning units based on primitive data patterns; and the learning units integrating clusters selected from the group consisting of: neural networks; mixtures of Gaussians; support vector machines; Kernel functions; genetic programs; decision trees; hidden

Markov models; independent component analysis; principle component analysis; and other learning regimes (page 1175, right column, lines 6-11; the tree used for classification is a decision tree).

At the time of the invention, it would have been obvious to a person of ordinary skill in the art to include the hierarchical data structure used in the learning algorithm from Tsishkou (page 1174, left column, lines 13-16; page 1175, right column, lines 6-10) and use it as a pattern-recognition algorithm in Bright (col. 6, lines 7-9) using the same motivation as in claim 18 above.

Claim 21

Bright teaches a method for modeling data as set forth in claim 20, wherein the hierarchy of learning units provide machine intelligence (col. 6, lines 1-9; use of pattern-matching algorithms implies machine learning, *i.e.* a machine has learned to recognize specific image patterns).

Claim 22

Bright teaches a method for modeling data as set forth in claim 20, wherein the primitive data patterns include a specific class of data (col. 6, lines 1-9, using a set of predefined texture patterns; pattern-recognition implies classification, which inherently uses data that belongs to a specific class).

Claim 23

Bright teaches a method for modeling data as set forth in claim 22, wherein the specific class of data is selected from the group consisting of: 2-dimensional data; 3-dimensional data; and N-dimensional data where N is greater than 3 (col. 6, lines 1-4; texture patterns are 2-dimensional data).

Claim 33

Bright teaches a method for compressing data as set forth in claim 32.

Bright does not expressly teach that the non-linear adaptive filter further comprises: a hash-function data-structure based on prioritization of tessellations, the prioritization based on available information within and surrounding a tessellation with the prioritization of the tessellation for processing being higher according to higher availability of the available information.

Tsishkou teaches the non-linear adaptive filter further comprises: a hash-function data-structure based on prioritization of tessellations, the prioritization based on available information within and surrounding a tessellation with the prioritization of the tessellation for processing being higher according to higher availability of the available information (page 1175, right column, lines 6-11; the data structure is disclosed as a tree based on tessellation).

At the time of the invention, it would have been obvious to a person of ordinary skill in the art to include the hierarchical data structure used in the learning algorithm

from Tsishkou (page 1174, left column, lines 13-16; page 1175, right column, lines 6-10) and use it as a pattern-recognition algorithm in Bright (col. 6, lines 7-9) using the same motivation as in claim 18 above.

Claim 34

Bright teaches a method for compressing data as set forth in claim 32.

Bright does not expressly teach that the non-linear adaptive filter further comprises: a hierarchy of learning units based on primitive data patterns; and the learning units integrating clusters selected from the group consisting of: neural networks; mixtures of Gaussians; support vector machines; Kernel functions; genetic programs; decision trees; hidden Markov models; independent component analysis; principle component analysis; and other learning regimes.

Tsishkou teaches that the non-linear adaptive filter further comprises: a hierarchy of learning units based on primitive data patterns; and the learning units integrating clusters selected from the group consisting of: neural networks; mixtures of Gaussians; support vector machines; Kernel functions; genetic programs; decision trees; hidden Markov models; independent component analysis; principle component analysis; and other learning regimes (page 1175, right column, lines 6-11; the tree used for classification is a decision tree).

At the time of the invention, it would have been obvious to a person of ordinary skill in the art to include the hierarchical data structure used in the learning algorithm from Tsishkou (page 1174, left column, lines 13-16; page 1175, right column, lines 6-10)

and use it as a pattern-recognition algorithm in Bright (col. 6, lines 7-9) using the same motivation as in claim 18 above.

Claim 35

Bright teaches a method for compressing data as set forth in claim 34, wherein the primitive data patterns include a specific class of images (col. 6, lines 1-9, using a set of predefined texture patterns; pattern-recognition of images implies classification, which inherently uses data that belongs to a specific class of images).

Claim 43

Bright teaches a method for modeling data using adaptive pattern-driven filters (Abstract, modeling is disclosed as compressing data), comprising:

applying an algorithm to data to be modeled based on an approach selected from the group consisting of: computational geometry (col. 4, lines 42-47; disclosed as a compression algorithm that works by geometrically splitting the image); artificial intelligence; machine learning; and data mining;

the data to be modeled selected from the group consisting of: 2-dimensional still images; 2-dimensional still objects; 2-dimensional time-based objects; 2-dimensional video; 2-dimensional image recognition; 2-dimensional video recognition; 2-dimensional image understanding; 2-dimensional video understanding; 2-dimensional image mining; 2-dimensional video mining; 3-dimensional still images; 3-dimensional still objects; 3-dimensional video; 3-dimensional time-based objects; 3-dimensional object recognition;

3-dimensional image recognition; 3-dimensional video recognition; 3-dimensional object understanding; 3-dimensional object mining; 3-dimensional video mining; N-dimensional objects where N is greater than 3; N-dimensional time-based objects; sound patterns; voice patterns (col. 4, lines 42-47; compressing video image data); generic data of generic nature wherein no specific characteristics of the generic data are know to exist within different parts of the data (col. 3, lines 7-10; disclosed as compressing general image data comprising of pixels arranged in a grid); and class-based data of class-based nature wherein specific characteristics are known to exist within different parts of the class-based data, the specific characteristics enabling advantage to be taken in modeling the class-based data (col. 6, lines 1-13; images having a "textured" appearance, classification matches repeated patterns of pixels);

an overarching modeling meta-program generating an object-program for the data; the object-program generated by the meta-program selected from the group consisting of: a codec, a modeler, and a combination of both (col. 8, lines 9-15; a color encoding model implies a codec for compressing-decompressing colors);

the data is modeled to enable the data being compressed for purposes of reducing overall size of the data (col. 1, lines 12-17);

the algorithm applied to the data including providing a linear adaptive filter adapted to receive data and model the data that have a low to medium range of intensity dynamics (col. 3, lines 54-58; disclosed as the part of the algorithm that performs subdivision into triangles), providing a non-linear adaptive filter adapted to receive the data and model the data that have medium to high range of intensity

dynamics (col. 6, lines 1-13; disclosed as the part of the algorithm that performs pattern recognition to map texture patterns), and providing a lossless filter adapted to receive the data and model the data not modeled by the linear adaptive filter and the non-linear adaptive filter, including residual data from the linear and non-linear adaptive filters (col. 7, lines 23-41; using Huffman lossless compression);

linear adaptive filter including tessellation of the data including tessellation of the data as viewed from computational geometry (col. 4, lines 42-54; since the tessellation is done using a geometric algorithm, it belongs to computational or algorithmic geometry), the tessellation of the data selected from the group consisting of planar tessellation and spatial (volumetric) tessellation (col. 5, lines 8-17; disclosed are both forms of tessellation, since each triangle has its own plane with a Z component);

the planar tessellation including triangular tessellation (col. 5, lines 8-17);

the spatial tessellation of the data comprises tessellation selected from the group consisting of tetrahedral tessellation and tessellation of a 3-dimensional geometrical shape (col. 5, lines 14-17; each triangle defines a 3-d plane, forming a 3-dimentional shape. Adjusting 3-d triangles form a tetrahedral);

the tessellation of the data achieved by a methodology selected from the group consisting of: a combination of regression techniques; a combination of optimization methods including linear programming; a combination of optimization methods including non-linear programming; a combination of interpolation methods (col. 5, lines 30-47; disclose the use of interpolation);

the tessellation of the data executed by an approach selected from the group consisting of breadth-first, depth-first, best-first, any combination of these (col. 6, lines 34-36; disclose a depth-first approach), and any method of tessellation that approximates the data subject to an error tolerance (col. 5, lines 49-54; using a similarity threshold);

the tessellation of the data is selected from the group consisting of Peano-Cezaro decomposition, Sierpiski decomposition, Ternary triangular decomposition, Hex-nary triangular decomposition, any other triangular decomposition, and any other geometrical shape decomposition (col. 5, lines 8-17);

the non-linear adaptive filter including a filter modeling non-planar parts of the data using primitive data patterns including a specific class of data selected from the group consisting of: 2-dimensional data; 3-dimensional data; N-dimensional data where N is greater than 3 (col. 6, lines 1-4; texture patterns are 2-dimensional data);

the modeling of the non-planar parts of the data performed using a methodology selected from the group consisting of: artificial intelligence; machine learning; knowledge discovery; mining; and pattern recognition (col. 6, lines 1-13; using pattern recognition);

providing a set of tiles approximating the data (col. 5, lines 8-17);

providing a queue of the set of tiles for input to the non-linear adaptive filter (col. 6, lines 34-36; processing tiles in a specific order implies queuing);

the non-linear adaptive filter processing each tile in the queue (col. 3, lines 50-51);

for each tile selected, the non-linear adaptive filter determining if the selected tile is within a tolerance of error (col. 3, lines 38-44);

for each selected tile within the tolerance of error, the tile is returned as a terminal tile (col. 3, lines 38-40); and

for each selected tile outside the tolerance of error, the selected tile is decomposed into smaller subtiles which are returned to the queue for further processing (col. 3, lines 54-58); whereby

the data is modeled to enable better manipulation of the data (col. 2, lines 52-55).

Bright does not expressly teach the non-linear adaptive filter including a hash-function data-structure based on prioritization of tessellations, the prioritization based on available information within and surrounding a tessellation with the prioritization of the tessellation for processing being higher according to higher availability of the available information, and including a hierarchy of learning units based on primitive data patterns, the hierarchy of learning units providing machine intelligence, the learning units integrating clusters selected from the group consisting of: neural networks; mixtures of Gaussians; support vector machines; Kernel functions; genetic programs; decision trees; hidden Markov models; independent component analysis; principle component analysis; other learning regimes;

training the non-linear adaptive filter at a time selected from the group consisting of: prior to run-time application of the non-linear adaptive filter; at run-time application of

the non-linear adaptive filter, the non-linear adaptive filter becoming evolutionary and self-improving.

Tsishkou teaches the non-linear adaptive filter including a hash-function data-structure based on prioritization of tessellations, the prioritization based on available information within and surrounding a tessellation with the prioritization of the tessellation for processing being higher according to higher availability of the available information (page 1175, right column, lines 6-11; the data structure is disclosed as a tree based on tessellation), and including a hierarchy of learning units based on primitive data patterns (page 1174, Fig. 3, mosaic blocks from the indexed database), the hierarchy of learning units providing machine intelligence, the learning units integrating clusters selected from the group consisting of: neural networks; mixtures of Gaussians; support vector machines; Kernel functions; genetic programs; decision trees; hidden Markov models; independent component analysis; principle component analysis; other learning regimes (page 1175, right column, lines 6-11; the tree used for classification is a decision tree);

training the non-linear adaptive filter at a time selected from the group consisting of: prior to run-time application of the non-linear adaptive filter; at run-time application of the non-linear adaptive filter, the non-linear adaptive filter becoming evolutionary and self-improving (page 1174, left column, lines 13-16; page 1175, right column, lines 6-10; the filter is self-improving by training a tree used for image classification).

At the time of the invention, it would have been obvious to a person of ordinary skill in the art to include the hierarchical data structure used in the learning algorithm from Tsishkou (page 1174, left column, lines 13-16; page 1175, right column, lines 6-10)

and use it as a pattern-recognition algorithm in Bright (col. 6, lines 7-9) using the same motivation as in claim 18 above.

Claim 44

Bright teaches a method for compressing data, comprising:

providing a linear adaptive filter adapted to receive data and compress the data that have low to medium energy dynamic range, the linear adaptive filter including tessellation of the data (col. 3, lines 54-58; disclosed as the part of the algorithm that performs subdivision into triangles);

the tessellation of the data selected from the group consisting of planar tessellation and spatial tessellation, wherein the planar tessellation of the data comprises triangular tessellation (col. 5, lines 8-17) and wherein the spatial tessellation of the data comprises tetrahedral tessellation (col. 5, lines 14-17; each triangle defines a 3-d plane, forming a 3-dimentional shape. Adjusting 3-d triangles form a tetrahedral);

the tessellation of the data selected from the group consisting of breadth-first, depth-first, best-first, any combination of these (col. 6, lines 34-36; disclose a depth-first approach), and any method of tessellation that approximates the data filtered by the linear adaptive filter within selectably acceptable limits of error (col. 5, lines 49-54; using a similarity threshold);

the tessellation of the data selected from the group consisting of Peano-Cezaro decomposition, Sierpiski decomposition, Ternary triangular decomposition, Hex-nary

triangular decomposition, any other triangular decomposition, and any other geometrical shape decomposition (col. 5, lines 8-17);

providing a non-linear adaptive filter adapted to receive the data and compress the data that have medium to high energy dynamic range (col. 6, lines 1-13; disclosed as the part of the algorithm that performs pattern recognition to map texture patterns);

the non-linear adaptive filter including a filter modeling non-planar parts of the data using primitive image patterns, the primitive image patterns including a specific class of images (col. 6, lines 1-9, using a set of predefined texture patterns);

providing a lossless filter adapted to receive the data and compress the data not compressed by the linear adaptive filter and the non-linear adaptive filter (col. 7, lines 23-41; using Huffman lossless compression);

providing a set of tiles approximating the data (col. 5, lines 8-17);

providing a queue of the set of tiles for input to the non-linear adaptive filter (col. 6, lines 34-36; processing tiles in a specific order implies queuing);

the non-linear adaptive filter processing each tile in the queue (col. 3, lines 50-51);

for each tile selected, the non-linear adaptive filter determining if the selected tile is within a tolerance of error (col. 3, lines 38-44);

for each selected tile within the tolerance of error, the tile is returned as a terminal tile (col. 3, lines 38-40);

for each selected tile outside the tolerance of error, the selected tile is decomposed into smaller subtiles which are returned to the queue for further processing (col. 3, lines 54-58); whereby

such that data is being compressed for purposes of reducing its overall size (col. 1, lines 12-17).

Bright does not expressly teach the non-linear adaptive filter including a hash-function data-structure based on prioritization of tessellations, the prioritization based on available information within and surrounding a tessellation with the prioritization of the tessellation for processing being higher according to higher availability of the available information;

the non-linear adaptive filter including a hierarchy of learning units based on primitive data patterns, the learning units integrating clusters selected from the group consisting of: neural networks; mixtures of Gaussians; support vector machines; Kernel functions; genetic programs; decision trees; hidden Markov models; independent component analysis; principle component analysis; other learning regimes.

Tsishkou teaches the non-linear adaptive filter including a hash-function data-structure based on prioritization of tessellations, the prioritization based on available information within and surrounding a tessellation with the prioritization of the tessellation for processing being higher according to higher availability of the available information (page 1175, right column, lines 6-11; the data structure is disclosed as a tree based on tessellation);

the non-linear adaptive filter including a hierarchy of learning units based on primitive data patterns, the learning units integrating clusters selected from the group consisting of: neural networks; mixtures of Gaussians; support vector machines; Kernel functions; genetic programs; decision trees; hidden Markov models; independent component analysis; principle component analysis; other learning regimes (page 1175, right column, lines 6-11; the tree used for classification is a decision tree).

At the time of the invention, it would have been obvious to a person of ordinary skill in the art to include the hierarchical data structure used in the learning algorithm from Tsishkou (page 1174, left column, lines 13-16; page 1175, right column, lines 6-10) and use it as a pattern-recognition algorithm in Bright (col. 6, lines 7-9) using the same motivation as in claim 18 above.

Conclusion

The prior art made of record and not relied upon is considered pertinent to applicant's disclosure. Barnsley et al. (US Patent No. 5,065,447) teaches compressing digital images using tessellation. Deering (US Patent No. 5,793,371) teaches method and apparatus for geometric compression of three-dimensional graphics data. Deering (US Patent No. 5,867,167) teaches compression of three-dimensional graphics data including quantization, delta-encoding, and variable-length encoding. Kostrzewski et al. (US Patent No. 6,167,155) teaches method of isomorphic singular manifold projection and still/video imagery compression. Pardas et al. (US Patent No. 6,516,093) teaches

segmented video coding and decoding method and system. Corwin et al. (US Patent No. 6,529,635) teaches shape-based image compression/decompression using pattern matching. Xiaolin Wu et al. teaches “A Segmentation-Based Predictive Multiresolution Image Coder”. Riccardo Distasi et al. teaches “A B-Tree Based Recursive Technique for Image Coding”. Hebert et al. teaches “Fast Fractal Image Compression with Triangulation Wavelets”.

Contact Information

Any inquiry concerning this communication or earlier communications from the examiner should be directed to Sergey Datskovskiy whose telephone number is (571) 272-8188. The examiner can normally be reached on Monday-Friday from 8:30am to 5:00pm.

If attempts to reach the examiner by telephone are unsuccessful, the examiner's supervisor, Anthony Knight, can be reached on (571) 272-3687. The fax phone number for the organization where this application or proceeding is assigned is 571-273-8300.

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you have questions on access to the Private PAIR system, contact the Electronic Business Center (EBC) at 866-217-9197 (toll-free).

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